International Conference on Secure Information Systems and Technologies (ICSIST-2026)
DVD Part Number: CFP266BX-DVD; ISBN: 979-8-3315-8388-0

Liver Tumour Detection and Segmentation through Graph Neural Network Enabled Optimized Model (GNN-EOM)

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Abstract— **Early detection and accurate classification of tumours remain critical challenges in medical image analysis, particularly due to complex spatial relationships and heterogeneous tumour structures. The proposed approach leverages the MICCAI dataset to develop an effective graph neural network (GNN)–enabled optimized model for early tumour detection and classification. In this framework, medical images are transformed into graph representations where nodes capture salient anatomical and pathological features and edges encode spatial and contextual relationships among regions of interest. The GNN architecture exploits these relational dependencies to enhance feature learning beyond conventional convolution-based methods. To further improve performance, an optimization strategy is incorporated to refine network parameters and improve convergence, leading to robust generalization across varying tumour shapes, sizes, and intensity distributions. Experimental evaluation on the MICCAI dataset demonstrates that the proposed model achieves improved detection accuracy, reliable tumour classification, and enhanced sensitivity to early-stage abnormalities. The results indicate that graph-based learning provides a promising direction for next-generation intelligent diagnostic systems, supporting clinicians with more precise and early tumour assessment.**

Keywords—Liver Tumour, Artificial Intelligence, Human computer interface, Cognitive analysis, Neural network.

I. INTRODUCTION

Liver tumor has become one of the most common diseases among people, where early detection and accurate classification of tumor, plays an optimum role in enhancing the patient survival rate and are also helpful for the timely intervention of clinical procedures. Recent developments in medical imaging techniques, such as Magnetic Resonance Imaging (MRI), computed tomography (CT), and physiological imaging techniques, are helpful in accurately diagnosing and monitoring tumour progression levels. On the other hand, an increasing number of medical images creates complexity in making manual interventions, wide radiologist. The images captured from MRI and CT equipment are large in number and cause a delay in diagnosing the disease manually. consequently development of an automated Framework with the help of computer-aided diagnosis has created considerable attention in extracting the parameters of the tumor detected area, including handcrafted features, texture intensity, shape descriptors, and deep feature points to classify.

When these methods utilised in the proposed approach created moderate success the performance of the system is limited by making feature selection, and generalization across various dataset.

Utilization of deep learning algorithm in which convolutional neural network (CNN) architecture is utilised for classifying the medical images through deep learning-based model exactly extracts the tumour and segment the regions and make classification effectively keeping multiple benchmark dataset. Keeping the results of training from a convolution network architecture and primary grid structured data is simply having the ability to create special relationships, creating structural data extraction, which makes crucial classification of shapes with heterogeneous textures and complex interactive surrounding tissues. Capturing the structures and regional relationships, the early detection of liver tumors is being visualised and create the impact on the issue area measurement effectively.

Graph-based neural network architecture is considered for current research to make a powerful modelling of multiple images through a meaningful connection between the features and make an analytical relationship that is helpful for making the classifications using deep learning algorithms accurately. The deep capture of graph-based structure creates medical imaging Classifications accurately by making the disease-dependent modelling related to each feature and comparing the features by making meaningful mappings with the help of statistical metrics.

The major challenges in existing approaches towards early tumour detection, which act as smaller lesions not accurately detected by the system, with the poorly contrasted regions embedded in a complex structure of analytical regions, make it difficult to act as a strong feature for making the classification. Highlights of the advanced Framework are implemented to have a global structure enabled classification, which overcomes the challenges present in the existing Framework. Motivating these challenges, the presented approach with graph neural network enabled an optimization model for early detection of tumors using the MICCAI dataset is being discussed. The proposed approach extracts the salient features of the tuber images and compares them with the special relationship, as well as the Global features, to make a deterministic analysis on early-stage tumour identification.

In order to improve learning efficiency and classification accuracy of the proposed graph neural network based Image classification system, and Optimisation strategies are implemented to fine-tune the network parameters by making as stabilized convergence towards the feature mappings. The major contributions of the system are developed with a novel graph-based representation of medical images in which the tumor-related structures are classified. The graph neural letter architecture is derived from the learning framework team provide early detection and multi-classification. Optimise the training strategies developed to enhance the robustness of the feature extraction process that leverages the liver tumor detection process using the MICCIA dataset. The extensive experiments developed here outperform conventional deep learning algorithms in terms of accuracy and sensitivity.

The remainder of this paper is organized as follows. Section II reviews related work on tumour detection and graph-based learning methods. Section III describes the proposed GNN-enabled optimized framework in detail. Section IV presents experimental results and performance evaluation on the MICCAI dataset. Finally, Section V concludes the paper and outlines potential directions for future research.

The rest of the paper is formulated as existing scholarly articles learning in Section II, system tools required for implementation and dataset details in Section III, the design methodology and suggestion model-oriented discussions are made in Section IV etc.

II. BACKGROUND STUDY

D. -Y et al. (2023) The author presented a system in which a novel slice fusion enabled a global structural relationship model is implemented to extract the tissues present in the city slices and symbolize the features to the adjacent slices to make the important parameter of the tissues using a masked recurrent neural network(Masked-RCNN) architecture for tumour detection. The presented approach considers that the LITS data set contains metastasis of tumour cells. The presented approach is demonstrated with various tumour-positive values and implements a segmentation process, comparing with various existing state-of-the-art approaches. The major challenge with the dataset is that the increased processing delay due to the CNN architecture consumes more GPU space. The images collected from the CT scans and MRI scans are high definition, thus performing with high-intensity data features. [7].

A. Kumar et al. (2024) The author presented a deep learning framework to detect the liver tumor using computer tomography images using convolutional neural network architecture. The proposed methodology focused on preprocessing steps includes contrast improvement noise reduction and deep image scaling to enhance the quality of liver tumour images. The system resize the images before involving the image into classification process for the apply histogram equalisation for noise removal. The image segmentation process involved in the presented approach provides binary classification model 10 classify the city images into winning and malign to tumors. In case of severe tumor constraints present in the test images the classification process deep extract the progression level of tumor and combine the methodology with the deep learning algorithm with image processing to make a comprehensive analysis on liver tumour analysis. [8].

L. Chen et al. (2026) The Other presented a intelligent early detection of tumor detection and surgical navigation system in which various collision of tools and surgical evaluations or analysed. The proposal system is developed as a early warning of coalition detection model during the tumor detection process in which the mathematical valuations create a distance between the surgical path and different shapes of tumor present inside the images 95% accuracy in terms of detecting that tumor [9].

A. Krishan et al. (2021) The Other presented algorithm in which two step process is developed where enhancement of CT images using contrast controlled adaptive histogram out of equalisation algorithm is implemented for the decision making model is implemented using convolutional neural network. The overall curiosity of the presented approach is actually around 94% where the experiment result is applied in terms of making the feature extraction process more automative and reduces the processing time by 10.5% over all the linear decrease of feature extraction make the complete processing time get reduced the reduces the assistant or radiologist. [10].

Z. Xue et al., (2021) proposed model can achieve feature interaction across multi-modal channels by sharing the down-sampling blocks between two encoding branches to eliminate misleading features. Furthermore, we combine feature maps of different resolutions to derive spatially varying fusion maps and enhance the lesions information. In addition, we introduce a similarity loss function for consistency constraint in case that predictions of separated refactoring branches for the same regions vary a lot. We evaluate our model for liver tumor segmentation using a PET-CT scans dataset, compare our method with the baseline techniques for multi-modal (multi-branches, multi-channels and cascaded networks) and then demonstrate that our method has a significantly higher accuracy ( ) than the baseline models [11].

H. Seo et al. (2021) Deep learning is becoming an indispensable tool for imaging applications, such as image segmentation, classification, and detection. In this work, we reformulate a standard deep learning problem into a new neural network architecture with multi-output channels, which reflects different facets of the objective, and apply the deep neural network to improve the performance of image segmentation. By adding one are more interrelated auxiliary-output channels, we impose an effective consistency regularization for the main task of pixelated classification (i.e., image segmentation). Specifically, multi-output-channel consistency regularization is realized by residual learning via additive paths that connect main-output channel and auxiliary-output channels in the network [12].

III MATERIALS AND METHODS

A.MICCIA Dataset

The MICCAI liver database has become a popular reference point in comparing automated liver tumour detection and segmentation algorithms because of its high clinical significance and annotations of experts. The dataset is comprised of contrast-enhanced images of the abdominal CT of various patients that have considerable variability in the shape, size, and appearance of the tumours and in the quality of the images. The tumours in the MICCAI dataset have a tendency to appear in varied forms, such as low contrast with the surrounding liver tissues, irregular and discontinuous boundaries, and massive variation in size and position in different slices. Moreover, the dataset has cases that have more than one tumour and textures of heterogeneous lesions, which makes it difficult to extract features and make classification consistent. Intra-and inter-patient variability and class imbalance of healthy liver tissues and tumour tissues also pose difficulties on learning models especially in detection of early tumours in which lesions do not cover large areas. The combination of these conditions makes the MICCAI liver dataset a challenging testbed and it demands sophisticated learning methods with the ability of strong feature representation, spatial relationship modeling, and effective generalization based on challenging clinical environments.

B. Methodology

The suggested system as shown in figure 1 commences with the acquisition of liver CT images on the MICCAI dataset and takes them through a thorough preprocessing pipeline to increase the data consistency and the quality of discriminative features. The images are then resized to a constant spatial resolution so that all inputs have equal sizes, and then augmentation is done by rotation to enhance orientation invariance. To equalize the intensity differences between scans, histogram equalization is used to enhance the contrast between tumour and normal liver tissues. These are then enhanced utilizing image quality improvement algorithms and data augmentation is applied to augment the effective image volume and reduce class imbalance.

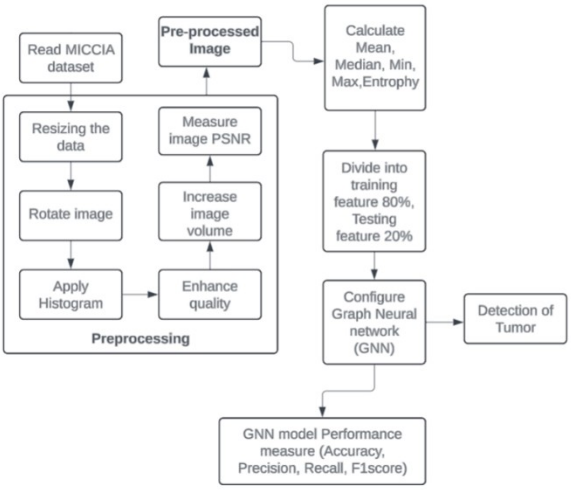

Fig 1. System architecture

Quality of preprocessing is qualitatively tested through the measurement of peak signal-to-noise ratio (PSNR) which yields a set of diagnostically sound images. After preprocessing, every picture is converted to graph-based representation so as to permit non-Euclidean learning. Super-pixels (salient regions) extracted out of the image are modeled as the graph nodes with each node corresponding to the feature vector, which is a combination of first-order statistical and texture descriptors, such as the mean, median, minimum, maximum, and entropy values. The anatomical continuity and contextual relationships within liver tissue is represented by the formation of an adjacency structure based on the spatial proximity and feature similarity criteria between nodes to define the edges between nodes.

The construction of this graph allows one to explicitly model the intra-liver interactions and tumour-tissue interactions, which are hard to model with conventional convolutional architectures. The graph features are extracted to create both training and testing subsets based on 80:20 split so as to maintain fair performance estimation. The graph neural network (GNN) is set up in a way that it is used to pass messages through networked nodes with each node periodically combining information about its neighbours to update its feature representation. This relational learning process can provide the model the capacity to differentiate the tumour areas by using both local variations in intensities and global structural context. The optimized GNN model is trained to generate graph node classification as tumour and non-tumour graph. Aggregation of the node-level predictions in order to obtain image-level decisions leads to the final tumour detection output. Model performance is assessed using accuracy, precision, recall, and F1-score metrics, validating the effectiveness of the graph-based learning framework for early liver tumour detection.

Algorithm 1: GNN-Based Liver Tumour Detection Using MICCAI Dataset

Input:
MICCAI liver CT image dataset D
Output:
Tumour detection and classification results with performance metrics
Begin
Load MICCAI liver dataset $D = \{I_1, I_2, \dots, I_N\}$
For each image $I \in D$ do
    Resize image I to fixed resolution
    Apply rotation-based data augmentation
    Perform histogram equalization on I
    Enhance image quality using contrast enhancement
    Increase image volume using augmentation techniques
    Compute PSNR to validate preprocessing quality
    Store preprocessed image I_p
End For
For each preprocessed image I_p do
    Segment image into salient regions / super-pixels
    Initialize graph $G = (V, E)$
For each region $r \in I_p$ do
    Create node $v \in V$
    Extract node features:
        $f(v) = \{mean, median, min, max, entropy\}$
    End For
Establish edges E based on spatial proximity and feature similarity
End For
    Split dataset into training set (80%) and testing set (20%)
    Configure Graph Neural Network (GNN) architecture
    Train GNN
For each epoch do
    Perform message passing and feature aggregation
    Update node embeddings using learnable weights
    Minimize classification loss
End For
Test GNN
Predict tumour / non-tumour labels for test graphs
Aggregate node-level predictions to image-level tumour detection
Compute performance metrics: Accuracy, Precision, Recall, F1-score
Return detection results and performance measures
End

Table 1. GNNEOM layer specifications

Layer	Input	Operation	Output
1	(X, A)	Graph Convolution + ReLU	(H^1)
2	(H^1, A)	Graph Convolution + ReLU	(H^2)
3	(H^2, A)	Graph Convolution	Node embeddings / predictions

Table 1 shows the various layer stacks associated for GNNEOM development. The input layer is the hybrid Graph convolution model, embedded with different graphical relativity connected with the features.

IV RESULTS AND DISCUSSIONS

Figure 2 illustrates sample test images selected from the MICCAI liver dataset used for model evaluation. The images represent contrast-enhanced abdominal CT slices exhibiting diverse liver anatomies, intensity variations, and tumour appearances. The selected test samples include variations in tumour size, shape, and location, highlighting the complexity of liver tumour detection under realistic clinical conditions. These images are used to assess the generalization capability of the proposed GNN-based framework on unseen data and to validate its effectiveness in detecting tumour regions across heterogeneous imaging scenarios.

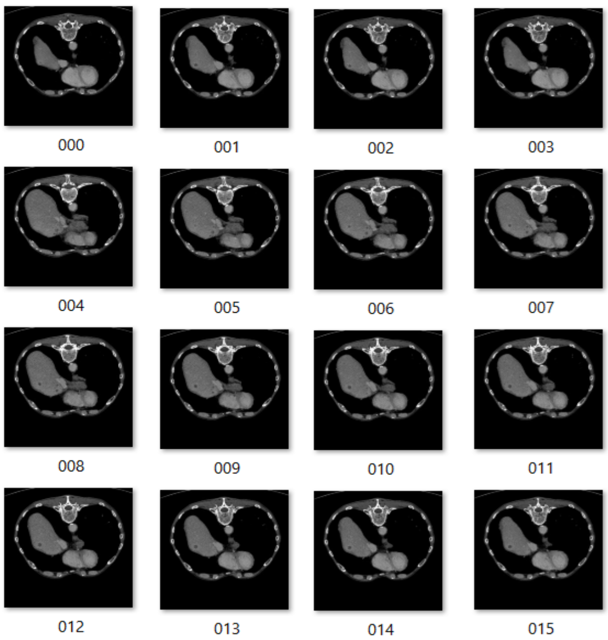

Fig 2 Input MICCIA dataset test images

Figure 3 shows the Consistency-Aware Natural-Looking Histogram Equalization (CANHE) resullt. It shows the enhanced image outcome for analysis in which CANHE model is developed for enhancing the input test images.

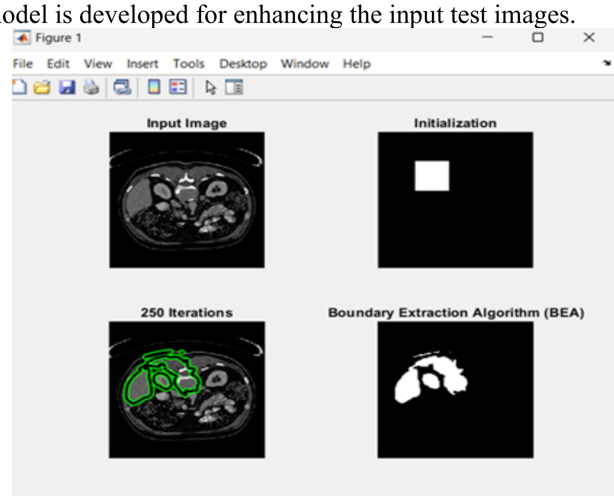

Fig.3 CANHE Results

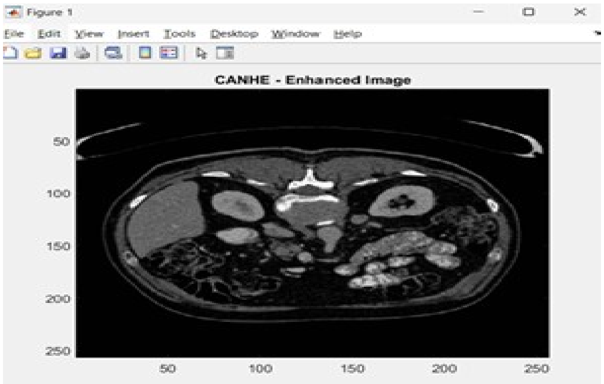

Fig 3. Enhanced images using CANHE model

Fig 4. Segmentation

Figure 4 shows the segmentation of tumor impacted area by making a number of iterations using boundary extraction algorithm (BEA). The presented architecture after the segmentation process evaluates the segmented area size and tissue extraction area which is considered as one of the features for making the analysis.

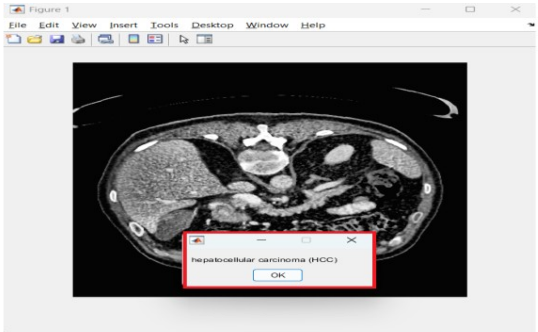

Fig 5. Classification of Tumour

Figure 5 shows the classification of Liver tumour, where different types of tumours are classified based on the input test images using GNN-EOM. The system evaluates the accurate detection and classification of liver tumour by making 10-fold cross validation process. The system is optimized since the analysis process is validated through 10-fold validation process.

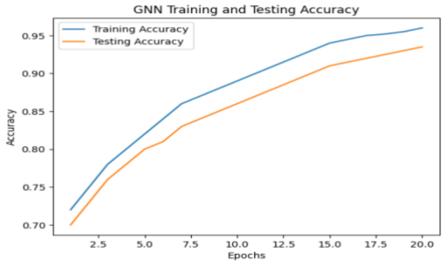

Fig 6. Training accuracy

Figure 6 illustrates the training and testing accuracy of the proposed GNN-based liver tumour detection model across epochs. The close alignment between training and testing accuracy demonstrates strong generalization capability. The training accuracy of proposed GNN-EO model in which the training accuracy for each and every image considered for testing and operation when the epochs increases, accuracy of the system increases and reaches till 95%. Maximum accuracy is reached during the 20 epoch of the total iteration due to the unique features extracted from the dataset.

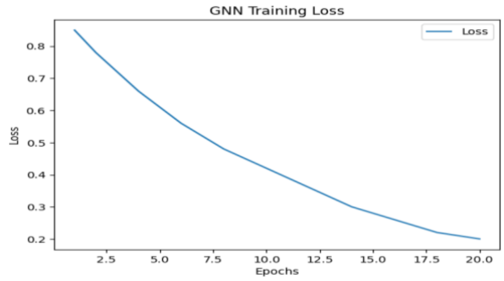

Fig 7. Training Loss

Figure 7 presents the corresponding training loss curve, which decreases consistently, indicating stable and effective optimization of the GNN parameters. The graph shows the training loss of the proposed GNN-EO model where the loss of the training process reduces, completely degraded to zero as the number of iterations increased through epochs. The Optimisation is applied when the number of correlated features towards the disease impacted patient data, and normal data get converged. The GNN-EO parameters are evaluated using the accuracy, precision, Recall and F1Score.

Table 2. Comparison of proposed GNN-EOM with Existing SOA

Model / Method	Approach	Dataset / Task	Key Metrics
Two-Stage CNN (Duo-Stage	CNN attention with two-stage	LiTS segmentati on	Dice: ~0.967; Tumor:

Attention)	(liver–tumor)		~0.725
FasNet (Uncertainty)	Hybrid CNN + uncertainty model	LiTS17 segmentation	Dice: ~0.748
ResUNet Variant	Residual + U-Net with uncertainty U-Net	3DIRCADb segmentation	Dice: ~75.8%
CNN Classification (Multi-Feature)	Traditional ML + feature optimization	CT classification	Accuracy ~97.5% (MLP best)
Deep Binary CNN	Deep binary CNN classification	Multiple tumors (various)	High specificity
STC (HCC vs ICC)	Hybrid CNN + RNN	Multi-phase CT	AUC ~0.86–0.93
Classical CNN CRF (Older)	Cascaded FCN + CRF	CT / MRI lesion segmentation	Dice ~0.94
Deep Learning (Diagnostic Model)	Deep CNN segmentation + evaluation	Clinical CT scans	Dice: ~0.967; Precision: ~0.967
Graph Neural Network Optimization Model (EOM)	Neural network combined with 10-fold cross-validation	LiTS dataset	~96% Accuracy

Table 2 shows the comparison of proposed method GNN-EOM with existing state of art approaches. The existing methods such as CNN model, achieved 96% accuracy towards LiTS Liver tumour dataset, two-stage DCUNet are utilized. The methodology provides smaller structure segmentation. The same dataset with fasNet (hybrid CNN with attention network is considered and achieved the accuracy of 74.8%. CNN with multi-feature model is achieved with 97.7% accuracy. Deep CNN with multiple tumour images achieved 98.6% accuracy. STIC model with Multi-phase CECT image dataset achieved 86.2% accuracy. Cascaded FCN model with MRI images of Liver achieved 94% accuracy. Similarly deep learning with Clinical CT images achieved 98.7% accuracy. The proposed method GNN-EOM achieved 96% accuracy towards LiTS dataset with optimized approach enhance the processing time.

V CONCLUSION

Liver tumor has become one of the life-threatening healthcare disease impact humans, facing various challenges in recent days. The need for effective evaluation of liver tumor segmentation with accurate detection of infected area, analysis of tissue in packs is important to stabilize the patient for further treatment. The proposed framework considers parameters for making the analysis more accurate and effective. The presented data is collected from the MICCAI dataset, where the liver images are high resolution and provide deep structural information about the tumour-impacted area. The proposed graph neural network-based feature extraction process enables the system to extract the deep structural features and analyse the relationship between the features with normal patients and the deep knowledge driver liver infected patients to make the classification more accurate comparing with existence date 96% accuracy towards Liver tumour detection and classification using GNN model.

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